Data and the Aggregate Economy

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While the data economy has changed the way people shop and businesses operate, it has only just begun to permeate economists' thinking about aggregate economic phenomena. In the early twentieth century, economists like Schultz (1943) analyzed agrarian economies and land-use issues. As agricultural productivity improved, production shifted toward manufacturing. Modern macroeconomics adapted with models featuring capital and labor, markets for goods, and equilibrium wages (Solow, 1956).

Once again, productivity improvements have shifted the nature of production. In the information age, production increasingly revolves around information and, specifically, data. The United Nations (2017) estimates that as of 2015, global production of information and communications technology (ICT) goods and services amounted to approximately 6.5% of global GDP, and roughly 100 million people were employed in the ICT services sector alone. This raises the question of how macroeconomists might incorporate data as a service, an input or as an asset.

This article explores the various ways that the growth of data interacts with classic macroeconomic questions concerning topics such as GDP measurement, monetary neutrality, growth, and firm dynamics; it describes tools we already have to understand the data economy; and it compares and contrasts two frameworks that integrate data in a standard macroeconomic environment.

What do we mean by data? Data is information that can be encoded as a binary sequence of zeroes and ones. Of course, that includes an enormous spectrum of knowledge, not all of which is the subject of this article. For example, music, poetry, technological breakthroughs, patents, and

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ideas about efficient management or operations can all be digitally encoded. These are not the types of digital information typically accumulated by the big data revolution. Instead, much of big data is records or evidence of transactions. It is personal information about online buyers, satellite images of traffic patterns near stores, textual analysis of user reviews, click-through data, and other evidence of economic activity that is used to forecast sales, earnings, and the future value of firms and their product lines.

We begin in Section 1 by describing recent innovations in data tech that prompted much big data discussion. Section 2 catalogues evidence about the importance of such digital information and how it affects various facets of the macroeconomy. But precise measurement of the data economy is beset by conceptual challenges: How should we value data? How should we price digital services, many of which are offered at a zero price, in exchange for the user's data? Should we change the way we measure GDP? These questions cannot be answered with more economic data. They are conceptual challenges that require a rigorous, conceptual framework in order to make sense of them. Section 3 describes theoretical tools and ideas from related literatures that we can use to understand data. It explores the ways in which data is similar to and different from technology. It also describes tools from the information frictions literature we can use to understand the mechanisms at work in the data information economy. Finally, Section 4 embeds tools from both the growth and information frictions literatures in equilibrium frameworks. It presents and compares two frameworks that shed light on the conceptual questions surrounding the measurement of data and of aggregate economic activity. We then revisit the facts we laid out in Section 2 to expand on our two presented frameworks and show how they can be utilized to analyze how data has impacted the macroeconomy.

1 Innovations in Data Technology

The concept of utilizing data is not new — many popular techniques have been around for decades. Why then has the focus on data been so prominent lately? The answer lies in improvements in computing power that help companies process data faster, innovations in infrastructure that allow more data to be stored more cost effectively, and most of all, progress in machine learning techniques. Combined with the increasing availability of larger volumes and varieties of data, these advances have led to the popularity of using big data to generate insights (SAS Institute, 2019). Business has adopted big data and machine learning techniques for a variety of applications from advertising, to making faster and more accurate business decisions, to automating manual processes. In the asset management industry, such computational techniques have made investment decisions that rival those of humans (Abis, 2017).

One form of data processing is artificial intelligence (AI), which can be defined as: machines that display responses to stimulation, including cognitive decision-making processes, that are similar to conventional responses from humans (Shubhendu and Vijay, 2013). Recently, artificial intelligence has been in the news for outperforming humans. One prominent example involves Go, a game considered to be much more complex than chess. For a long time, Go has been used to show that advances in artificial intelligence have not been large enough to rival human intelligence. In recent years, Google's DeepMind developed artificial intelligence called AlphaGo that beat the world's top ranking Go players using strategies that it learned in a matter of days that took several thousand years for humans to develop (MIT Tech, 2017).

In an economic context, data is starting to play an important role in improving firms' decision-making. Goldfarb and Tucker (2019) discuss the reduction of economic costs in the following five activities: search, replication, transportation, tracking, and verification. Bajari, Chernozhukov, Hortasu, and Suzuki (2018) study one particularly intensive data user, Amazon. They use Amazon's data to examine the accuracy of forecasts by firms in two dimensions: the number of products (N), and the number of time periods for which a product is available for sale (T). Their empirical results indicate gains in forecast improvement in the T dimension, but a flat N effect. The firm's overall forecast performance, controlling for N and T effects across product lines, has improved over time, suggesting gradual improvements in forecasting from the introduction of new models and improved technology. Firms have also benefited from data decreasing the cost of storing, computing, and transmitting data.

2 Evidence of the Effect of Data in Macroeconomics

The technological progress in data processing has not gone unnoticed by economists. The data economy has impacted every corner of macroeconomic research. This section catalogues facts that speak to these changes. These lines of research are still in their early stages. These facts raise many questions for additional research.

2.1 Measuring GDP and the Size of the Data Economy

The data economy is large. By 2017, e-commerce had reached 8% of consumption. The savings of travel costs from substituting to online merchants yielded the equivalent of a 1% permanent boost to consumption (Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best, 2019). However, not all the gains in well-being arising from digital goods and services are captured by measures of gross domestic product (GDP).

One missing component from national accounts is the value of zero-price goods, which are prevalent in the digital economy. Brynjolfsson, Collis, Diewert, Eggers, and Fox (2019) introduce a new metric, GDP-B, which quantifies and captures the welfare contributions of these goods. Through incentive compatible choice experiments, they show that welfare gains from Facebook add about 0.05-0.11 percentage points to GDP-B growth per year in the US. Brynjolfsson, Eggers, and Gannamaneni (2018) use online choice experiments to measure consumers' willingness to accept compensation for losing access to various digital goods and show that losing access to all search engines or all email services for one year, for instance, generates disutility equivalent to earning $500-$1,000 less per year.

Often, such zero-price digital goods are not truly free. They are services offered in exchange for data. This is a barter trade, where the service is being bartered for personal data. Barter is not measured by GDP.

Digital service innovations are also not fully captured by traditional GDP measures. Byrne and Corrado (2019) propose a framework for measuring digital services improvements, specifically in the context of advancements made in providing consumers content, by incorporating capital service flows that improve existing GDP measures of personal consumption. With their new measure, Byrne and Corrado (2019) show that these content delivery services increased consumer surplus by almost $1,800 per connected user per year and contributed over one-half percentage point to US real GDP growth in the last 10 years.

A framework that attempts to capture the digital value that GDP misses is Hulten and Nakamura (2017)'s model of information goods as "output-saving." Information technology like e-commerce reduces the need for traditional consumer goods and services, such as transportation, that would otherwise be captured in GDP. Since the electronic component of e-commerce itself has no explicit price, it is not captured in GDP. Since these goods reduce our need for value that would otherwise be measured in GDP and are not themselves counted, they bypass GDP and create consumer surplus directly. The authors propose a concept of expanded GDP (EGDP) that combines the conventional GDP measure with a willingness-to-pay metric of the value of output-saving innovation to consumers. This new metric suggests that living standards, as measured by EGDP, rose at a faster rate than real GDP growth.

Data also increases measured GDP of non-data firms by increasing productivity. Brynjolfsson, Hitt, and Kim (2011) find that firms that adopt data-driven decision-making (DDD) have output and productivity that is 5%-6% higher than what would be expected given their other investments and information technology usage. The relationship between DDD and performance also appears in other performance measures such as asset utilization, return on equity, and market value.

One active area of debate is whether the difficulty of measuring the digital economy can explain the productivity slowdown. Brynjolfsson, Rock, and Syverson (2017) postulate four data-related explanations for the productivity slowdown, which has exceeded 1% per year for more than a decade: false hopes about AI, mismeasurement, redistribution, and implementation lags. Of the four hypotheses, the last one —the fact that AI has not yet diffused widely—has been the biggest contributor, according to the authors. In contrast, Syverson (2017) argues that surplus from ICT is not large enough to explain much of the productivity slowdown. Data advancements have also led to novel ways to measure various macroeconomic variables. Improved image and data processing of satellite night lights data have notably been useful in improving upon GDP measures in countries where traditional data tends to be of poor quality or is generally unavailable (Henderson, Storeygard, and Weil, 2012).

Data and digital goods and services certainly present multiple measurement challenges. These challenges are both practical and conceptual. Research and practice will have to adapt for our measures of aggregate economic activity to remain accurate.

2.2 Growth, Development, and Trade

The rise of the data economy has promoted global economic fluidity, reducing language and geographical barriers. As a result, this digital age could present opportunities for new countries to emerge as potential key players in the economy. At the same time, the increased connectedness between countries has led to concerns about how best to regulate sharing data across borders.

The rise of a data-driven economy has raised fundamental questions about exporting and tariff policy, that are at the center of current trade negotiation. Control of data has become a significant issue in trade negotiations. Given that consumers' data is not priced, every transaction with a foreign company results in an asset, consumers' data, being given away to foreign firms. One new argument for tariffs that arises in the modern economy is that they compensate the home country for the value of the unpriced data being transferred. Another rationale for tariffs is that the economies of scale in data and the economies of scope and knowledge externalities in AI innovation could create the opportunity for country-level rents and strategic trade policy (Goldfarb and Trefler, 2018).

In international trade, data can reduce border frictions by decreasing language frictions and by lowering transportation costs. Both could help poor, remote countries benefit more from data. Using eBay, the American e-commerce company, as the study sample, Brynjolfsson, Hui, and Liu (2018) finds that the introduction of a machine translation system has significantly increased international trade, raising exports by 17.5% through a reduction in translation-related search costs. It is also clear that transportation costs of data and digital goods are quite different from those of traditional goods. Transporting data requires a large, fixed investment of IT infrastructure at the country level. However, even in many of the poorest countries, privately owned mobile phone networks already exist to carry data. Once some data infrastructure is in place, it may not be free to use, but its cost is nowhere near that of the road, sea or air transport of a stream of physical goods. Many remote countries have been held back by the difficulty of physically transporting goods to markets where the goods are valued. If these countries can develop the human capital to produce digital goods and services, they may be able to overcome their locational and physical infrastructure impediments. As a result of lower language barriers and the negligible marginal cost of transporting digital goods, many policy makers hope to capitalize on advantages offered by the digital economy to help their countries leapfrog. For instance, President Paul Kagame of Rwanda introduced his plan for the National Information and Communication Infrastructure policy by claiming: "In Africa, we have missed both the agricultural and industrial revolutions and in Rwanda we are determined to take full advantage of the digital revolution. This revolution is summed up by the fact that it no longer is of utmost importance where you are but rather what you can do ..." Pushing for policy that promotes development of knowledge, skills, and infrastructure for information and communications technology, President Kagame expressed his hopes that such innovations would help bring Rwanda to the forefront of the global economic competition (Government of Rwanda, 2010).

Finally, the growing economic importance of data raises a related question of how data impacts economic growth and development. Is this a one-time level shift in utility or a new engine of growth? Nordhaus (2015) explores the question of whether AI brings us close to economic *singularity*—an increase in economic growth at an accelerating pace, resulting from growth in computation and artificial intelligence. In particular, he evaluates the substitutability between information and conventional inputs along seven different metrics and concludes that singularity is not near. Even though certain tasks can be easily automated, several non-routine tasks remain a bottleneck.

2.3 Pricing and Monetary Neutrality

One reason firms use data is to set prices. Online stores can do this easily with algorithms to automatically adjust prices. This shift in pricing technology therefore improves price flexibility. But since monetary policy efficacy depends on price rigidity, the digital economy might reduce monetary policy effectiveness. Gorodnichenko and Talavera (2017) find that price changes occur more frequently in online stores (once every three weeks or less) than in regular stores (once every 4-5 months or more). Such an increase in price flexibility could alter the real effect of monetary policy.

Huang and Sundararajan (2011) analyze a model of usage pricing for digital products with discontinuous supply functions. Modeling digital goods as goods with zero variable costs and periodic fixed costs, the authors show that the discontinuous cost structure can be accrued as a virtual constant variable cost. They then investigate the optimal technology capacity planning and find that the widely adopted full cost recovery policies are typically suboptimal.

Data is also transforming the banking sector. Vives (2019) explores how data technology has increased efficiency and service in the banking industry, but also how it has raised concerns about consumers' data protection. These competing forces will challenge regulators to balance the needs of innovation and privacy as they oversee the industry's transformation.

2.4 Firm Dynamics

A prevalent trend in the macroeconomy is that firm sizes are increasing. In the last 30 years, the proportion of those employed at firms that have been in business for less than five years has dropped from 13% to less than 8% and the share of those employed at firms with fewer than 100 employees has declined from 40% to 35%. Meanwhile, the percentage of employment at firms with more than 1,000 employees has increased from 25% to 33%. For firms in the top 5% percentile of revenues, their revenues rose from 57% to 67% of the revenue share (Davis and Haltiwanger, 2019).

While all firms can benefit from new data technologies, some may benefit more than others. In particular, larger, older firms seem to benefit more. This increases the competitiveness of such firms, making competition harder for smaller, newer firms. This matters for industry dynamics.

One reason that data may affect firm dynamics is that it can broaden the span of control in firms, which favors larger firms. Aghion, Bergeaud, Boppart, Klenow, and Li (2019) argue that ICT innovations in the 1990s allowed high-productivity firms to profitably expand. This expansion came at the cost of labor and of small firms. The authors argue that it produced a decline in business dynamism and a fall in the labor share of income.

Another reason that data interacts with firm size is that financial data may be changing the firm size distribution. Begenau, Farboodi, and Veldkamp (2018) argue that the use of big data in financial markets can significantly lower the cost of capital for large firms, relative to small ones. Cheaper financing enables large firms to grow larger. Large firms, with more economic activity and a longer firm history offer more data to process, making large firms more valuable targets for data analysis. Once processed, that data can better forecast firm value, reduce the risk of equity investment, and thus reduce the firm's cost of capital. As big data technology improves, large firms attract a more than proportional share of the financial data processing, enabling large firms to invest cheaply and grow larger.

Evidence in support of the effect on firm dynamics comes from firms' investment in IT resources. Tambe and Hitt (2012) use data on IT productivity to show that IT returns are substantially lower in midsize firms than in Fortune 500 firms. However, IT returns also materialize more slowly in large firms, whereas in midsize firms, the short-run contribution of IT to output is similar to the long-run output contribution. They also find that the measured marginal product of IT spending is higher from 2000 to 2006 than in any previous period, suggesting that firms, and especially large firms, have been continuing to develop valuable uses of IT.

Brynjolfsson and McElheran (2016*b*) find that DDD adoptions by manufacturing plants in the US nearly tripled (from 11% to 30%) between 2005 and 2010. In a companion paper, Brynjolfsson and McElheran (2016*a*) find that adoption of DDD is earlier and more prevalent among larger, older plants belonging to multi-unit firms. Smaller single-establishment firms adopt later but have a higher correlation with performance than similar non-adopters. The average value-added for later DDD adopters is 3% greater than for non-adopters. DDD-related performance differentials decrease over time for early and late adopters, consistent with firm learning and development of organizational complementarities.

2.5 Labor Demand

Another important question about the macroeconomy is how new data technologies will impact the allocation of and demand for labor. One possible effect to be explored is that machine learning could facilitate employer-employee matching. Reduced frictions might lower unemployment.

Another possible effect is labor replacement. Furman and Seamans (2018) document a large increase in AI and robotic-related activity in the economy. The McKinsey Global Institute estimates that established firms spent between $18 billion and $27 billion on internal corporate investment in AI-related projects in 2016 (Bughin, Henke, Chui, Manyika, Saleh, Wiseman, and Sethupathy, 2017). As computers and robots can do more of the work that people used to do, automation and AI likely contribute to the divergence between GDP and private employment, also called the "Great Decoupling" (Brynjolfsson and McAfee, 2013).

Acemoglu and Restrepo (2018) construct a framework for the study of the impact of AI on the labor market. They emphasize the displacement effect, which reduces demand for labor and wages, and the productivity effect, which increases demand for labor in non-automated tasks. This is further complemented by additional capital accumulation and deepening automation, both of which increase the demand for labor. Nevertheless, the net effect is likely to be a reduction in the share of labor in national income as automation increases output per worker more than wages. Creation of new labor-intensive tasks also reinstates labor in new activities and increases the labor share to counterbalance the impact of automation. The authors also highlight risks in such a transition. One risk is a mismatch between workers' skills and the skills required to use new technologies. A second risk is the possibility that automation undermines the introduction of other productivity-enhancing technologies.

Using a different approach, Bessen (2018) presents a simple model where a changing elasticity of demand explains the U-shaped pattern in unemployment in the textile, steel, and automotive industries. Initially when products are expensive, consumers are priced out of the market and demand elasticity tends to be high. As technological change drives down prices and increases income, the demand elasticity of those products declines, which leads to higher demand and lower unemployment in the respective industries.

AI and automation will likely impact labor demand in various industries differently. Brynjolfsson and Mitchell (2017) identify eight types of tasks that are suitable for machine learning systems, namely: (1) the task involves learning a function that maps well-defined inputs to well-defined outputs, (2) the task involves large data sets that exist or can be created, (3) the task provides clear feedback with definable goals and metrics, (4) the task does not require long chains of logic that depend on diverse background knowledge, (5) the task does not require detailed explanation, (6) the task provides high tolerance for errors, (7) the function being learned does not change rapidly over time, (8) the task does not require specialized dexterity, physical skills, or mobility.

Arrieta Ibarra, Goff, Jimnez-Hernndez, Lanier, and Weyl (2018) explore labor-related concerns. These include fears that AI will displace workers as well as concerns that a slowdown in AI applications could slow productivity growth. The authors advocate treating users who trade their personal data in exchange for digital services as laborers and producers of the digital goods, as opposed to simply consumers. They argue that counteracting the current data monopsonist-dominated system with features such as competition, a data labor union, or regulatory measures to encourage payment of users providing data will greatly help remedy labor market problems, political problems and the potentially problematic interactions between the two.

3 Existing Tools for Understanding the Data Economy

Since the literature on data and macroeconomics is nascent, we should consider which ideas from related literatures are relevant. Three literatures in particular guide much of the existing theory work: the literature on growth theory, technological progress and learning-by-doing; the literature on information frictions; and the literature on intangible capital. By comparing data to ideas, human capital, signals, and intangible capital, we can see what existing knowledge is portable to this new domain.

3.1 Ideas and Tools from the Literature on Growth and Technology

Comparing Data and Technology Data and technology have some important similarities. Data is used by firms to make strategic decisions that enhance their productivity and profitability. Modern firms use data to decide which locations to close or open, which product lines to cut, and to forecast which new goods will enjoy high demand. Like technology or total factor productivity (TFP) in standard economic models, firms use data to take a given set of inputs and produce more valuable outputs.

Another key similarity between data and technology is that both are nonrival. Just as many firms can make use of an idea at the same time, many firms can use the same data. Of course, the value of data is affected by how intensively others use it, just as the value of widget production is affected by the number of widget producers in the economy. But if a widget is a physical good, one person's use of it typically precludes another's simultaneous use of the same widget. Widgets are rival. Since data can be freely copied, this is not the case for data. The nonrivalry of data creates a force for increasing returns. These increasing returns are important because they may favor larger firms, larger investors and larger economies.

However, data and technology are not the same. One important difference is that data and technology are produced in different ways. Creating new technology requires resources: skilled labor, perhaps a laboratory, new good prototypes, and perhaps many failures before a successful technology is discovered. In contrast, data is a by-product of economic activity. Producing and selling generates data about the volume of sales, the means of payment, and characteristics of buyers. Sometimes collecting and processing data to extract knowledge is costly. But data is not typically produced in a lab. More data comes from more economic activity. This difference in production matters. One of the fundamental insights of Romer (1990) is that monopolies are necessary to incentivize idea production. This is not true of data production. Because data is a by-product of economic transactions, no extra incentives are needed for its production.

Other differences between data and technology are the ways in which they leak and their patent protection. We know that ideas or technologies leak (Easterly, 2002). Workers at garment factories in Bangladesh take their ideas to start their own firms. When they are hired away by competitors, Silicon Valley workers take their technological knowledge with them. But data is not embodied in one's mind. It is too complex, too nuanced, too extensive for that. A worker might steal data from their firm. But that is a crime. The data is not embodied in their human capital. This feature is also what distinguishes data from human capital or forms of learning-by-doing. Conversely, some ideas are illegal to take from one firm to another. These are ideas that are protected by patents. But patents do not protect data. There are no legal institutions designed specifically to ensure the exclusive right of one entity to use a particular set of data. At the same time, because data does not easily leak, and because protection is not needed to incentivize the creation of data, such an institution is probably not needed.

Lower leakage of knowledge encoded as data is important for growth. It also could explain one of the most important trends in the US macroeconomy, the decrease in business dynamism. In a recent working paper, Akcigit and Ates (2019) study the sources of this declining dynamism and find that the primary cause is the decline in knowledge diffusion from the largest to the smallest firms. Thus, if data lends itself to less diffusion than traditional technologies, then the growing data economy could be responsible for the decline in firm dynamism.

Finally, the ability to monetize data and the widespread sale of data also distinguishes it from technology. A few features of data lend themselves well to such transactions. First, a seller can clearly describe the contents of a data set, without revealing its information content. A buyer can know exactly how many users or clicks or transactions from which stores or websites, how much revenue is involved, which images are analyzed or text parsed, and still not know what the data will say. Second, data can be easily split. One can sell 1,000 data points or 999, or however much the buyers is willing to pay for. As mentioned above, data is less likely to leak. That makes it a more desirable purchase.

Similar to technologies, data can be sold both directly and indirectly. A data vendor can sell you a data set directly, by transferring the binary code that constitutes the data. But they can also offer data services, which are an indirect sale of data. Such a service might entail using their data to place your ad on the screen of a particular user type; it could entail using their data to choose assets to invest your money in, or it could involve using proprietary data to provide a firm strategic business consulting advice. Such services monetize data, without transferring the underlying data used in the service.

Models of Data as Technology A few authors have analyzed the impacts of big data and AI on growth. Agrawal, McHale, and Oettl (2018) develop a combinatorial-based knowledge production function and embed it in the classic Jones (1995) growth model to explore how breakthroughs in AI could enhance discovery rates and economic growth. Lu (2019) embeds self-accumulating AI in a Lucas (1988) growth model and examines growth transition paths from an economy without AI to an economy with AI and how employment and welfare evolve. The authors show that AI can increase economic growth, and the evolution of AI increases household lifetime welfare in the long run.

Aghion, Jones, and Jones (2017) explore the role of AI in the growth process and its reallocative effects. Using Baumol (1967)'s cost disease insight, the authors argue that Baumol's cost disease leads to the traditional industries' declining share of GDP as they become automated, which is offset by the growing fraction of automated industry. This explains the observed stability in the capital share and per capita GDP growth over the past century despite evolving automation. In their model, labor share remains substantial because labor represents a bottleneck for growth. The authors also suggest that AI can increase growth of new ideas and potentially obviate the role of population growth in generating exponential economic growth. Nevertheless, even though AI can theoretically generate "singularity"—a notion that artificial super intelligence could trigger runaway technological growth and propel infinite income in finite time—growth may remain limited due to essential areas of production that are hard to improve. Moreover, AI may discourage future innovation for fear of immitation, undermining incentives to innovate in the first place.

Jones and Tonetti (2018) explore a growth economy where data is a by-product of economic activity and an input into productivity. They explore how different data ownership models affect the rate of economic growth. We describe their model in more detail below.

3.2 Ideas and Tools from Information Frictions

Data is information. We often refer to the transmission of information as a signal. Here are four ideas from the information frictions literature that use the language of signals, but can be easily adapted to think about data.

Rational inattention as a data processing allocation problem. In a way, models of data processing are already prevalent in strands of the macroeconomics literature. For example, one of the leading explanations for the real effects of monetary policy is costly information processing. Often referred to as rational inattention, following Sims (2003), such models consider what types of information or data is most valuable to process, subject to a constraint on the mutual information of the processed information and the underlying uncertain economic variables. The idea of using mutual information as a constraint, or the basis of a cost function, comes from the computer science literature on information theory. The mutual information of a signal and a state is an approximation to the length of the bit string or binary code necessary to transmit that information (Cover and Thomas, 1991). While the interpretation of rational inattention in economics has been mostly as a cognitive limitation on processing information, the tool was originally designed to model computers' processing of data. When we re-interpret rational inattention theories as data processing theories, we gain insights such as the notion that when firms have limited or costly data processing, they allocate their processing power optimally among data on various types of shocks. If they use the resulting knowledge to set prices, the aggregate response of prices to monetary shocks looks realistic (Maćkowiak and Wiederholt, 2009). Similarly, when investment managers allocate their data processing ability optimally across various types of financial data, and then choose portfolios of equities to invest in, this can explain features of portfolio returns and equilibrium asset prices (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016). Rational inattention has been applied to many more problems, all of which could be re-interpreted as data processing problems. Taking these models and growing the data processing capacity (as in Begenau, Farboodi, and Veldkamp (2018)) can give us new insights into the ways in which abundant data is reshaping macroeconomic forces.

Data as a by-product of economic activity. Veldkamp (2005), Ordonez (2013) and Fajgelbaum, Schaal, and Taschereau-Dumouchel (2017) all contain the idea that information is a by-product of economic activity and that firms use this information to reduce uncertainty and guide their decision-making. These authors did not call the information data. But it has all the hallmarks of modern transactions data. The data produced was used by firms to forecast the state of the business cycle. Better forecasting enabled the firms to invest more wisely and be more profitable. As such, these papers have early versions of a data-feedback loop whereby more data enables more production, which in turn, produces more data. These models restrict attention to data about aggregate productivity. In the data economy, that is not primarily what firms are using data for. But such modeling structures can be adapted so that production can also generate firm- or industry-specific information. As such, they provide useful equilibrium frameworks on which to build a data economy.

Direct and indirect sale of information. Once we start considering data as an asset and the sale of data as the sale of an asset, it leads to thinking about the booming information services or subscription economy. A small, older literature in finance explored the question of whether an owner of information should sell that information directly to investors, or whether they should use their information to manage the investors' portfolios for them, and charge a fee for the service. Admati and Pfleiderer (1990) consider this trade-off in the context of a noisy rational expectations financial market, not a goods market economy. Of course, a financial investment decision is not so different from firms' real investment decisions. Risky assets might be interpreted as product lines with uncertain profits. While many aspects of the model are finance-specific, the tools and lessons bear revisiting and importing into new models of the data macroeconomy.

Applying these tools could be important for macroeconomists because they could help with GDP measurement. A service flow is measured. Data as an asset might not be, if it is not sold or is bartered. Or it could be that when data is sold as an asset, the economic gains are booked immediately. Data sold as a service, gradually over time, might change the timing of the measurement of economic value. Just as economists impute housing services of owner-occupied housing to include it in GDP, one might think of imputing the value of a stream of data services as part of GDP measurement. To know how to do that, we need to know how to think about valuing such services.

Bias and the incentives to provide information. If information is sold, the incentives of the data provider may influence what content is provided. Nimark (2014) explains that unusual events are more likely to be reported in the news than commonplace ones. The author shows that such news reporting tendencies can explain changes in macroeconomic uncertainty and volatility. Furthermore, an increased level of news focused on the economy can not only increase an agent's uncertainty but also its sensitivity to the news information, too.

Gentzkow and Shapiro (2010) find that newspapers have an incentive to align the political leaning of their news with that of their readers, as opposed to that of the companies' owners. One reason is that Bayesian consumers tend to consider information to be higher quality when it comes from sources that confirm their prior expectations. Thus news media may be incentivized to align their slant to the prior beliefs of their consumers to gain a reputation for quality (Gentzkow and Shapiro, 2006). The same incentives that lead news outlets to choose some news to provide may apply to data providers. As we start to explore data sales, we should remember that data sellers are strategic actors.

3.3 Ideas from Intangible Capital

Data is also a form of intangible capital, though it is distinct from other forms of intangible capital because it poses different measurement issues. Intangible capital measures generally use the cost of investment to value the intangible capital stock. But data is a by-product of activity, with little or no creation cost. Though there is some cost associated with warehousing and processing, the data itself isn't created in a costly way, so it is often not counted as having positive value in the intangible capital stock.

There is a possible category on firms' balance sheets for data, allowing it to be considered intangible capital. If a firm buys data, it is clear that it should be valued at its market price. But if the firm produces its own data, its value may be determined at the firm's discretion. Intangible capital is a key component of the debates about investment stagnation, long-run increasing markups and productivity measurement.

In the investment literature on Q theory, Crouzet and Eberly (2018) build on Hayashi (1982) by adding intangibles as a different form of capital with a similar role, but not perfectly substitutable with tangible capital. They attribute the rise of intangible capital as the reason for the retail sector trend of increased investment in technology-driven business practices and therefore higher productivity despite weak investment relative to strong cash flow and valuation. Belo, Gala, Salomao, and Vitorino (2018) incorporate two types of intangible capital, knowledge capital and brand capital, into their neoclassical model of investment in order to study determinants of a firm's market value. They also note the declining importance of physical capital, in contrast with the growing importance of knowledge capital, over the past few decades.

Martinez (2018) focuses on a specific type of data intangible capital, automation capital, as an additional input with labor in a constant elasticity of substitution (CES) aggregate production function. Automation technology is modeled as a form of innovation that can replace labor with capital. The CES production function parameters depend on the distribution of automation technology across firms. The automation distribution is modeled as the measure of capital at each degree of automation associated with the firms. One can then show that given specific conditions on the automation distribution and its corresponding productivity distribution, the aggregate output in the model economy can be modeled with a CES production function that has elasticity of substitution between zero and one. The analysis concludes that while labor share might decline if the most automated firms automate more processes, labor share will actually increase when firms with lower degrees of automation increase their automation abilities. In contrast to the growth literature on data, this literature assumes that data has diminishing returns and functions like physical capital. It often acknowledges that some intangibles might be nonrival. It generally does not incorporate that into a view of the role of data in long-run outcomes. But this literature focuses more on measurement than the other two. As such, it offers measurement ideas that could be important for the macro-data agenda.

4 Modeling the Data Economy

The previous sections show how data interacts with many facets of the macroeconomy and provides ideas for how to model and measure data. What is only starting to emerge is a clear idea of how data is an integral part of the economy, both as an input into economic activity, and as a by-product of economic activity. An equilibrium framework with both features is valuable because it can explain the difference between price, cost, and the value of data and data-related goods.

One reason to use theory is that the economy is in the midst of a transition. Empirical work takes past trends or covariances and extrapolates to form predictions. But in transitions, the future often looks systematically different from the past. Another reason to model data is for policy analysis. Policy questions about privacy, trade, and firm competition all involve potential regulation of data. Such policy changes have equilibrium effects. We have no data from such alternative policy regimes with which to estimate these effects. Instead we need structural models, which we can estimate and then alter to perform policy counterfactual experiments.

Specifically, we compare two models. One treats data as information used to forecast an unknown state. The other models data as a nonrival good, equivalent to a new technology. In both models, data depends on the macroeconomy because it is a by-product of economic activity; it influences the macroeconomy because firms use it to improve their productivity.

When data is modeled as information used to forecast an unknown state, it will not be able to sustain perpetual growth. Also information-data is accumulated and has a value that can be expressed as parameters of the economy. While both models argue that there can be a region of increasing returns, data in the information-based model will eventually have returns that decrease, bringing data-driven growth to a halt.

4.1 A Model of Data as Information

The first model is a close adaptation of Farboodi and Veldkamp (2019), which builds on ideas sketched in Farboodi, Mihet, Philippon, and Veldkamp (2019*b*).

Model Setup Note that time is infinite and discrete. We index a unit continuum of competitive firms by i. Every firm i uses $k_{i,t}$ units of capital to produce $k_{i,t}^{\alpha}$ units of goods, each of which have quality $A_{i,t}$. We denote P_t as the equilibrium price of these goods with varying amounts of quality. The aggregate quality-adjusted supply is:

$$Y_t = \int_i A_{i,t} k_{i,t}^{\alpha} di. \tag{1}$$

The inverse demand function describes the market clearing price that declines as supply Y_t grows:

$$P_t = \bar{P} Y_t^{-\gamma}. \tag{2}$$

Firms treat the aggregate price P_t as given and their quality-adjusted goods are perfect substitutes. This means that if i's good is one-half the quality of j's, then two units of i's good are a perfect substitute to one unit of j's. The good's quality is important because firms will use data to improve quality. Quality $A_{i,t}$ is dependent on the firm's choice of a production technique $a_{i,t}$, and each firm has one optimal technique. That optimal technique has a persistent and a transitory component: $\theta_{i,t} + \epsilon_{a,i,t}$, neither of which can be separately observed. The persistent component $\theta_{i,t}$ follows an AR(1) process: $\theta_{i,t} = \bar{\theta} + \rho(\theta_{i,t-1} - \bar{\theta}) + \eta_{i,t}$, which firms can use data to learn about. $\eta_{i,t}$, the AR(1) innovation is *i.i.d.* over time. For simplicity, we assume here that $\eta_{i,t}$ is also independent across firms.[1] Meanwhile, the transitory shock $\epsilon_{a,i,t}$ is also *i.i.d.* across firms and time, but cannot be learned. The optimal technique is significant to a firm because it determines the quality of a firm's good. Quality $A_{i,t}$ depends on the squared difference between the firm's chosen production technique $a_{i,t}$ and the optimal technique $\theta_{i,t} + \epsilon_{a,i,t}$:

$$A_{i,t} = \bar{A}_i \left[\hat{A} - (a_{i,t} - \theta_{i,t} - \epsilon_{a,i,t})^2 \right]. \tag{3}$$

The role of data in this model is to help firms select better production techniques. One interpretation of this role is that data can, for example, inform a firm whether blue or purple shoes or gas or electric cars will be more valued by their consumers and as a result, allow the firm to produce accordingly. Transactions reveal these preferences. However, preferences are continually changing and firms must constantly adapt to them. Another interpretation is that data can help a firm to optimize its operations. It is also true that much data is used for advertising, which may not enhance aggregate output. Farboodi and Veldkamp (2019) show how to model data that is used for business stealing. They show that the firm dynamics results are unchanged. But of course, data that is simply a means for stealing others' business produces no aggregate economic growth. Data provides information on $\theta_{i,t}$. The purpose of the temporary shock ϵ_a in this model is to prevent

[1] Farboodi and Veldkamp (2019) relax this assumption. When the optimal technique is correlated across firms, then firms can learn from each others' data. In such an environment, firms choose to buy and sell data to other firms.

firms from learning $\theta_{i,t}$ through observation of their revenue at the end of period t. Without the inclusion of ϵ_a, the collection of past data would not be considered a valuable asset since the firm could maximize the quality of the good upon learning the current value of $\theta_{i,t}$ by setting $a_{i,t} = \theta_{i,t}$. The next assumption embodies the notion that data is a by-product of economic activity. We define $n_{i,t}$, the number of data points observed by firm i at time t, as a function of their production in the prior period, $k_{i,t-1}^{\alpha}$:

$$n_{i,t} = z_i k_{i,t-1}^{\alpha}, \tag{4}$$

where z_i is the parameter that denotes the "data-savviness" of a firm. Here, a data-savvy firm harvests lots of data per unit of output. For example, a firm that produces a simple mobile application, but harvests all the data on its consumers' phones has high z_i because it obtains many data points per unit of output. On the other hand, firms that do not track transactions have low or zero z_i. Each data point $m \in [1 : n_{i,t}]$ reveals the following signal:

$$s_{i,t,m} = \theta_{i,t} + \epsilon_{i,t,m}, \tag{5}$$

where $\epsilon_{i,t,m}$ is *i.i.d.* across firms, time, and signals. For ease of use, we assume a normal distribution for all the shocks in the model: fundamental uncertainty is $\eta_{i,t} \sim N(\mu, \sigma_\theta^2)$, unlearnable quality transitory shock is $\epsilon_{a,i,t} \sim N(0, \sigma_a^2)$, and signal noise is $\epsilon_{i,t,m} \sim N(0, \sigma_\epsilon^2)$.

Firm Problem. A firm makes a series of production and quality choices $k_{i,t}, a_{i,t}$ to maximize

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(P_t A_{i,t} k_{i,t}^{\alpha} - r k_{i,t} \right) \tag{6}$$

Belief updating for $\theta_{i,t}$ is done using Bayes' law. Firms observe the previous period's revenues and data each period, and then decide on capital level k and production technique a. The information set of firm i when selecting $a_{i,t}$ is denoted as $\mathcal{I}_{i,t} = [\{A_{i,\tau}\}_{\tau=0}^{t-1}; \{\{s_{i,\tau,m}\}_{m=1}^{n_{i,\tau}}\}_{\tau=0}^{t}]$. For simplicity, we assume the rental rate of capital is given. However, one can also embed an equilibrium context into this setup where capital markets are cleared or where one can add labor markets and endogenize the demand for goods. This model is only a theoretical sketch. It allows us to focus on the data-relevant mechanisms.

Solution The state variables of the model's recursive problem are (1) the beliefs about $\theta_{i,t}$, and (2) the precision of those beliefs. Solving the first order condition with respect to the technique choice, we arrive at the following optimal technique: $a^*_{i,t} = \mathbb{E}_i[\theta_{i,t}|\mathcal{I}_{i,t}]$. We then define posterior precision of beliefs as $\Omega_{i,t} := \mathbb{E}_i[(\mathbb{E}_i[\theta_{i,t}|\mathcal{I}_{i,t}] - \theta_{i,t})^2]^{-1}$ to get the expected quality $\mathbb{E}_i[A_{i,t}] = \bar{A} - \Omega_{i,t}^{-1} - \sigma_a^2$. Substituting for the optimal technique choice a^* allows one to eliminate the firm's expected value of $\theta_{i,t}$ as a state variable. We can then express expected firm value recursively.

Lemma 1 *The optimal sequence of capital investment choices $\{k_{i,t}\}$ solves the following recursive problem:*

$$\begin{aligned} V_t(\Omega_{i,t}) = \max_{k_{i,t}} \; & P_t\left(\bar{A} - \Omega_{i,t}^{-1} - \sigma_a^2\right) k_{i,t}^{\alpha} \\ & - rk_{i,t} + \beta V_{t+1}(\Omega_{i,t+1}) \end{aligned} \tag{7}$$

where $n_{i,t+1} = z_i k_{i,t}^{\alpha}$ and

$$\Omega_{i,t} = \left[\rho^2(\Sigma_{i,t-1}^{-1} + \sigma_a^{-2})^{-1} + \sigma_\theta^2\right]^{-1} + n_{i,t}\sigma_\epsilon^{-2} \tag{8}$$

Refer to Farboodi, Mihet, Philippon, and Veldkamp (2019*b*) for the proof. This result allows us to reduce our setup to a deterministic problem with only one state variable, $\Omega_{i,t}$, because expected quality $A_{i,t}$ depends on the conditional variance of $\theta_{i,t}$ and because our information structure can conform to the structure of a Kalman filter where the conditional variance sequence is deterministic.

Valuing Data Here, $\Omega_{i,t}$ can be thought of as the amount of data accumulated by the firm. While $\Omega_{i,t}$ is technically defined as the precision of the firm's posterior belief, according to Bayes' rule for normal variables, the posterior precision is the sum of the precision of prior beliefs and the precision of each signal observed: $\Omega_{it} = \rho^2\Omega_{i,t-1} + n_{it}\sigma_\epsilon^{-2}$. Subsequently, Ω is a linear transformation of n_{it}, the number of data points observed. The true amount of information in one unit of data is a vague concept that is difficult to quantify, so it makes sense to normalize signal precision to $\sigma_\epsilon^{-2} = 1$ as an alternative measure. Ω_{it} also captures the value of past observed data because it includes a term for the discounted prior precision, $\Omega_{i,t-1}$. Thus, the marginal value of an additional piece of data with precision 1 would be $\partial V_t/\partial \Omega_{it}$. Another feature for the model that one could explore is adding markets for buying and selling data, which would represent the firm's demand, i.e., its marginal willingness to pay for – or to sell – data. Consequently, one could infer parameters of the model using data sales prices.

Valuing zero-price goods The optimal price of a firm's good in this setting may be close to zero. The reason is that the firm wants to sell many units in order to accumulate data that will boost the productivity of future production. It could also be that the firm wants to accumulate data in order to sell it.

Measuring data. The model suggests two possible ways of measuring data. One is to measure output or transactions. If we think data is a by-product of economic activity, then a measure of that activity should be a good indicator of data production. Of course, that could be different from data use, if data is traded. But one can adjust data production for data sales and purchases to get a flow measure of data. Then, a stock of data is a discounted sum of data flows. The discount rate depends on the persistence of the market. If the data is about demand for fashion, then rapidly changing tastes imply that data has a short longevity and a high discount rate. If the data is mailing addresses, that market is quite persistent. An AR(1) coefficient of the variable being forecasted is sufficient to determine the discount rate.

The second means of measuring data is to look at what actions it allows firms to choose. A firm with more data can respond more quickly to market conditions than a firm with little data to guide it. To use this measurement approach, one needs to take a stand on what actions firms are using data to inform and what variable firms are using the data to forecast, and then measure both the variable and the actions. One example is portfolio choice in financial markets. Farboodi, Matray, Veldkamp, and Vekateswaran (2019*a*) use the covariance between prices and future earnings to infer the covariance between investment choices and future earnings. That covariance between choices and unknown states reveals how much data investors have about the future unknown state. A similar approach could be to use the correlation between consumer demand and firm production across a portfolio of goods to infer a firm's data about demand. Which approach is better depends mostly on the data available. One difference between the two is the units. Measuring correlation gives rise to natural units, in terms of the precision of the information contained in the total data set. The first approach of counting data points measures the data points more directly. But not all data is equal. Some data is more useful to forecast a particular variable. The usefulness or relevance of the data is captured in how it is used to correlate decisions and uncertain states.

4.2 A Model of Data as Productivity and the Social Benefits of Privacy

While the previous model equated data to signals about a random, unknown outcome, the next model equates data with productivity, technology or ideas. Units of data translate one-for-one into firm total factor productivity. At the same time, this model paints a richer picture of many of the characteristics of data—in particular the fact that data is nonrival and offers increasing return to scale. Such characteristics are essential for their main question: how policy makers should regulate data ownership. Jones and Tonetti (2018) show that in equilibrium, firms may not adequately respect the privacy of consumers. Because of nonrivalry, there may be large social gains to sharing data across firms, even in the presence of privacy considerations. However, fearing creative destruction, firms may choose to hoard data they own, leading to the inefficient use of nonrival data. They conclude that giving the data property rights to consumers can generate allocations that are close to optimal. Since this model covers data privacy issues, one relevant application for it is understanding how cybersecurity impacts the economy by raising the cost to sharing data and using data from consumers.

This second model is a simplified version of Jones and Tonetti (2018).

Model Setup Time is infinite and continuous. There are N_t varieties of consumer goods produced by N_t firms at each time period t. There is also a representative consumer with the following log flow utility at time period t:

$$u(c_t, x_{it}, \tilde{x}_{it}) = \log c_t - \frac{\kappa}{2}\frac{1}{N_t^2}\int_0^{N_t} x_{it}^2 di - \frac{\tilde{\kappa}}{2}\frac{1}{N_t}\int_0^{N_t} \tilde{x}_{it}^2 di \tag{9}$$

where c_t is the individual's consumption, x_{it} is the proportion of data on an individual's consumption of consumer good variety i that is used by firm i, and $\tilde{x}_{it}$ is the proportion of the consumer's data on good variety i that is shared with other firms that aren't the one producing variety i. Note that privacy costs are incorporated as a quadratic loss function with weights κ and $\tilde{\kappa}$ to represent the trade-off experienced between privacy and consumption. The individual gains utility from consumption of the good but loses utility from their data being directly used by the firm and shared with other firms. Firm i produced good variety i according to:

$$Y_{it} = \Omega_{it}^{\eta} L_{it} \text{ with } \eta \in (0,1) \tag{10}$$

where Ω_{it} is the amount of data used to produce good variety i and L_{it} is labor. Note that there are constant returns to scale in the competing input, labor, and increasing returns to scale when considering both labor and data together. The increasing returns arise from the nonrival property. All the workers at the firm are able to access the same pool of data available to make good variety i without depleting it. As in the previous model, data is created as a by-product of consumption. We define n_{it} as the amount of data created about variety i.

$$n_{it} = c_{it} L_t = Y_{it} \tag{11}$$

The amount of data, Ω_{it}, used by the firm is:

$$\Omega_{it} \leq \alpha x_{it} n_{it} + (1-\alpha) B_t \tag{12}$$

where the first term represents the amount of data on variety good i that firm i can use to produce while B_t is the aggregated bundle of data shared by other firms on other varieties of goods.

$$B_t = \left(N_t^{-\frac{1}{\epsilon}} \int_0^{N_t} \Omega_{sit}^{\frac{\epsilon}{\epsilon-1}} di \right)^{\frac{\epsilon}{\epsilon-1}} \text{ with } \epsilon > 1 \tag{13}$$

where $\Omega_{sit} = \tilde{x}_{it} n_{it}$ is the amount of data on good variety i that is shared with other firms for the production of their good varieties. Since data is nonrival, the bundle can be simultaneously used by other firms without being depleted. Note that the above expression is an inequality because in this setup, if consumers own the data, then they may restrict the amount of data that can be used by the firm (i.e., $x_{it} < 1$).

Firms exit through a random death process. A firm gets hit by an exit shock $\{0, 1\}$, where the probability of exit δ depends on how much of its data the firm shares with others. The idea is that firms who sell all their data lose some of their competitiveness and that makes them less likely to survive. This assumption means that not all firms are willing to share all of their data.

Their solution shows that the social output per person is proportional to economy size, raised to a power greater than one, due to both the standard preference of more variety and the result that the nonrival property of data increases returns. Larger economies that produce more data experience large gains because this data gets reused by firms to increase production. As data's importance in the economy increases, more resources are devoted to activities that create more data (i.e., production) as opposed to activities that don't (i.e., variety and firm entry).

Model Comparisons. Both models have similar production structures that treat data as a by-product of consumption and use data to augment productivity. The key difference is how data is mapped into productivity (A). In Farboodi and Veldkamp (2019)'s model,

$$A(\Omega) = \bar{A} - \Omega^{-1} - \sigma_a^2. \tag{14}$$

The model portrays data as a way to reduce forecasting error to zero. Reducing a forecast error has bounded value.

Meanwhile, in Jones and Tonetti (2018)'s model, the mapping from data to productivity is:

$$A(\Omega) = \Omega^{\eta}. \tag{15}$$

This models data as something that contributes to productivity in an unbounded way. The implication is that data accumulation is akin to idea accumulation.

In other words, Farboodi and Veldkamp treat data as contributing to prediction. Jones and Tonetti consider data as something that advances ideas. It is true that machine learning algorithms are ultimately prediction algorithms. They are designed to spot patterns in data and use it to predict likely outcomes. At the same time, artificial intelligence has impacted idea creation. In the health and medical industries, it is revolutionizing the way research and development (R&D) is performed in the lab by predicting which directions of research are likely to be fruitful. In areas where advances in drug discovery, chemistry, and material sciences are slowing and becoming more costly, the ability of deep learning algorithms to uncover complex insights and predictions more quickly and affordably has been key to pushing forward the research frontier and making investments in these areas more viable (MIT Tech, 2019).

A similarity of the two frameworks is that allowing the sale of data matters. Both models make assumptions to guarantee that not all data in the economy can be used to produce a given good. In Jones and Tonetti (2018), firms that share too much data are more likely to exit. Furthermore, consumers may limit the use of data, due to privacy concerns. In Farboodi and Veldkamp (2019), firms' data is either not relevant for others, or if it is relevant, then only one firm can use the data at a time. The reason for these costs and restrictions is that in a competitive market, where one firm's actions do not affect the market prices, all firms would want to sell all their data to all other firms. In the absence of any price impact, there is no cost to selling one's data. In order to model meaningful data sharing decisions by firms, a firm's decision must affect its market conditions. That implies some form of imperfect competition.

So, just like growth models with idea production, models of data production require some market power. But the reasons are quite different. Growth models require market power to provide benefits that induce firms to produce ideas. Data models do not need incentives to produce data because data is a by-product of economic activity. Instead, data models require market power to create costs to sharing data so that not all firms share all data.

Another important difference between the two models is data depreciation. In Jones and Tonetti (2018), data depreciates completely at the end of every period. That simplifies the problem by removing data as a state variable. This allows one to use the model to infer a flow value of data, but not to value data as an asset. Meanwhile, Farboodi and Veldkamp (2019) allow for the accumulation of data and introduce the idea of data depreciation. This provides a more traditional accounting approach to measuring and valuing data as an intangible asset.

Empirical Work on Data Regulation Empirical work has studied the policy and regulatory implications of a data-driven economy and the privacy and data-sharing concerns that come with it. Ramadorai, Uettwiller, and Walther (2019) find considerable and systematic variation in privacy policies along multiple dimensions including ease of access, length, readability, and quality, both within and between industries. Large firms with intermediate data intensity have longer, legally watertight policies, but they are more likely to share user data with third parties. Agrawal, Gans, and Goldfarb (2019) compile research on the economic effects of AI and mention several policy considerations, including: price discrimination, algorithmic collusion, data privacy, and security challenges.

4.3 Using the Model Frameworks to Answer Macroeconomic Questions

We now revisit the different ways data has impacted the macroeconomy through the lens of the two frameworks we just discussed.

Measuring GDP and the Size of the Economy Both models can be used to express the value of data. In Farboodi and Veldkamp (2019), the value function, $V(\Omega)$, expresses the value of the data stock Ω. Because the model has data accumulation, the distinction between the stock and flow of data lends itself well to adopting measures like the investment and stock of capital. In Jones and Tonetti (2018), production without data has zero value. Thus, in a way, that attributes the entire value of GDP to data. But, the technology function (15) could be easily adapted to have a positive lower bound, and give data a more plausible valuation. Both models suggest that the inflow of data, the analog to investment in an intangible asset, is determined by the sales of the firm.

Growth, Development, and Trade The ability to benefit from data surely depends on the local human capital. While Mankiw, Romer, and Weil (1992) show how to augment the Solow growth model with human capital, a similar exercise could add human capital to (14) or (15).

Both models provide guidance about how unpriced data transferred during international trade might be valued and taxed. The valuation issue is the same issue as GDP measurement. In order to explore taxation, one needs a framework where taxation is optimal. Costinot, Lorenzoni, and Werning (2014) develop a theory of capital controls between two countries where controls are set to dynamically manipulate terms-of-trade (the price of exports relative to imports). They show that optimal taxation on capital flows for a country depends on how quickly that country is growing relative to the rest of the world. One might substitute a stock of data for the capital stock to explore the optimal set of tariffs or controls on cross-country data flows.

Pricing and Monetary Neutrality The idea that data is a by-product of economic activity could be integrated in an existing model of price-setting with imperfect information. Having information come from production, rather than from an information allocation or attention allocation choice, may change the aggregate and cross-sectional predictions of the theory. Embedding these ideas in a standard new-Keynesian framework might provide guidance about potential future changes in the efficacy of monetary policy.

Firm Dynamics To study the role of data in the phenomenon of large firms growing larger, we can embed the current firm structure from Farboodi and Veldkamp (2019)'s model into a Hopenhayn (1992) industry equilibrium model which endogenously determines entry, exit, firm size, and general firm dynamics through a stationary equilibrium analysis. The firm's stock of data could replace the capital stock or complement it. Different data precision paths for different firms could reveal how the firms' overall forecast performance for product sales varies with size, firm age, and other firm characteristics.

Labor Demand Either model could be adapted so that it treats data and labor as substitutes. The idea would be that data can be used to train AI algorithms, which in turn, can substitute for human labor. Of course, different sectors have different degrees of substitutability. Making this change would allow us to study how wages, capital returns, and income inequality evolve as the data economy grows.

5 Conclusions

Data is changing how we think about measuring economic value. It is reducing the importance of borders with its lower transportation cost and ability to translate, it is changing price setting in ways that could affect monetary policy, and it is changing the functioning of labor markets and the distribution of the size of firms. We see evidence of all these changes in the literature studied here. But to predict how far-reaching these changes will be and how large they will eventually become, requires a framework for prediction. In the midst of structural transformation, projection of past trends into the future is not a reliable guide. Instead, we need structural models and theories to guide our thinking about the nature of this change. Since the goal of AI is to perform cognitive capabilities similar to that of a human, AI technology is often used to automate tasks that were previously performed by humans. Subsequently, we can adjust Jones and Tonetti (2018)'s model so that it treats data and labor as substitutes by using a linear production function. We use data as a proxy for AI because Jones and Tonetti (2018)'s model equates data with productivity and technology, which includes AI, and AI's effectiveness tends to improve when it can learn from more data inputs.

While data is affecting every corner of the economy, and evidence is accumulating that its effects are transformative, theories exploring the role and value of data are only just emerging. Two lines of research are bringing different tools and perspectives to the debate. From the growth literature come tools to think about nonrivalry, imperfect competition and the ownership of data. The models may also equate data with productivity. That makes data a source of increasing returns and perpetual growth.

The information frictions literature brings the perspective that data is fundamentally information. Information is a tool to reduce uncertainty about unknown outcomes. Machine learning and AI are prediction algorithms, not invention algorithms. They are designed to detect complex patterns and use those patterns to forecast future outcomes. This is a technology to resolve uncertainty. Resolving uncertainty has finite benefits. Infinite data brings perfect foresight. Foresight makes firms more profitable, perhaps much more profitable. But it does not allow a firm, and certainly not the aggregate economy, to produce arbitrarily large quantities or value of real goods. Only innovation can do that. The bounded benefits to data imply that there must be decreasing returns at some point. This does not mean that data will not facilitate growth. It may be that data is a complement to innovation. But, just like capital, data alone can only achieve a level improvement in GDP, not a sustained increase in the rate of growth. Whether data complements or substitutes for innovation is an important open question for future theoretical and empirical research.

The growth and information frictions points of view are not irreconcilable. New work is needed to bring the richness of the growth approach together with the acknowledgment that data is information and to deliver a fuller picture of the reality and the potential of the new data economy.

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